Combining Decision Support Methodologies to Diagnose Pneumonia

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***Objective**: To evaluate the performance of a computerized decision support system that combines two different decision support methodologies (a Bayesian network and a natural language understanding system) for the diagnosis of patients with pneumonia.*
***Design**: Evaluation study using data from a prospective, clinical study.*
***Patients**: All patients 18 years and older who presented to the emergency department of a tertiary care setting and whose chest x-ray report was available during the encounter.*
***Methods**: The computerized decision support system calculated a probability of pneumonia using information provided by the two systems. Outcome measures were the area under the receiver operating characteristic curve, sensitivity, specificity, predictive values, likelihood ratios, and test effectiveness.* ***Results**: During the 3-month study period there were 742 patients (45 with pneumonia). The area under the receiver operating characteristic curve was 0.881 (95% CI: 0.822, 0.925) for the Bayesian network alone and 0.916 (95% CI: 0.869, 0.949) for the Bayesian network combined with the natural language understanding system (p=0.01).*
***Conclusion**: Combining decision support methodologies that process information stored in different data formats can increase the performance of a computerized decision support system.*

INTRODUCTION

The computerized patient record captures, stores, and reports a large amount of patient data. For health care organizations the ongoing efforts to integrate, merge, and maintain patient related information is important, but is becoming an increasingly complex and difficult task to manage. At the same time health care providers are challenged by the increasing amount of patient information in the computerized patient record. The opportunity to review clinical data from a variety of locations, at times convenient to the user, facilitates easier and faster access to information. The ease of information access, however, does not guarantee improved decision making because the glut of data can obscure the pertinence of these data. The clinicians' task changes from hunting and collecting data to recognizing and filtering patient information by importance. The human decision making process is limited when large amounts of information must be considered at a single instance (1). Computerized decision support systems (CDSS) can assist health care providers in compiling and condensing many patient- and disease-specific data and can support the decision making process at the point of care (2,3).

The available and copious integrated patient information is necessary to provide clinicians with a complete view of the computerized patient record. The power of CDSSs to retrieve and process large amount of data in a short time period and the access to more complete and better integrated patient data improves the accuracy and appropriateness of computerized recommendations. To be able to provide accurate and appropriate recommendations, however, the data from the various sources need to be available in a computable and decidable format (4); some clinical data, however, are not.

Health care information is represented in a variety of data formats, such as descriptive and structured text reports, continuous and categorical data, and analog and digital signals. Clinicians are not challenged to process data that are represented in different formats. For CDSSs, however, each data format requires specialized algorithms, and such algorithms are frequently able to extract information from a single format category only. In a patient with chest pain, for example, the computerized analysis of an electrocardiogram is based on one data format only, but should be linked to clinical data, to a computerized analysis of the dictated radiology report, and possibly even include information from the pattern analysis of a patient's chest x-ray image.

Many institutions are experimenting with the computerization of clinical guidelines, which may ease their clinical implementation and promote dissemination for routine patient care. However, the computerization of guidelines frequently requires the integration of clinical variables that come from disparate data sources and are represented in a variety of formats. Linking different decision support methodologies that can process and combine data from various sources and formats could improve the computerization efforts of guidelines. However, relatively few attempts have been made to link different decision support methodologies that analyze and correlate patient data stored in different formats.

To provide decision support in the diagnosis and the management of pneumonia we separately developed and evaluated a Bayesian Network (BN) (5) and a Natural Language Understanding System (NLUS) (6). The BN included primarily numerical and coded data elements. The NLUS involved the processing of free text radiology reports only. All data elements are relevant in the diagnosis and the management of pneumonia patients, but each system was weak in the area where the other system was intended to be strong. Due to their complementary nature, we hypothesized that a combination of the two systems would provide more complete patient information in computable and decidable form.

In this study we examined whether the combination of the two decision support methodologies could improve the diagnostic performance of a CDSS designed to identify patients likely to have pneumonia in an emergency department (ED) setting.

BACKGROUND

Community-Acquired Pneumonia

Detection of pneumonia and prompt initiation of antibiotic treatment are important to reduce disease severity and mortality. The diagnosis and the management of pneumonia patients often take places within a short time period. It involves the interpretation of information that is captured in the computerized patient record in a variety of data formats. In the HELP clinical information system (7) the patient's age, vital signs, and laboratory results are stored as numerical values, nurse assessment and chief complaint are captured in coded format, the patient's present and past medical history is entered as short free text phrases, and the dictated chest x-ray reports are available in free text. Each data element contributes a different amount of information to the diagnosis and the management of pneumonia. The chest x-ray report, available in free text only, provides a substantial amount of information to the diagnosis (e.g., a new pneumonic infiltrate) and the management of pneumonia (e.g., the presence of a pleural effusion or multilobar involvement of an infiltrate) whereas the clinical data elements each add a smaller amount of information. In most cases a pneumonia diagnosis can only be supported if both a suggestive combination of clinical variables and a new pneumonic infiltrate on the chest x-ray exam are present. In contrast, a pneumonia diagnosis might remain inconclusive if a new opacity on the chest x-ray exam is not supported by clinical data.

Natural Language Understanding System

SymText is an NLUS that extracts clinical findings from radiological chest x-ray exams (8). The NLUS was able to accurately identify findings that are relevant for the automatic identification of pneumonia, such as the presence of a pneumonic infiltrate, and the computerization of pneumonia guidelines, such as the presence of a pleural effusion (6). The real-time evaluation of chest x-ray reports was supplemented by the implementation of a speech recognition system in the radiology department that reduced the availability of dictated reports in the ED from 12 to 2 hours (9). A 2-hour turnaround time meant that the radiologist's interpretation was frequently available during the patient's encounter in the ED. The timely availability of chest x-ray information influences diagnostic assessment and management decisions. The quick turnaround times for chest x-ray reports allowed the NLUS to process free text reports in real time. The NLUS based its interpretation on free text only and did not "correlate" the extracted findings with clinical data.

Bayesian network

We implemented a pneumonia CDSS that consists of a diagnostic and a management component (5). The diagnostic component is driven by a BN and computes a probability of pneumonia. The goal of the BN is to automatically identify patients suspected to have pneumonia during the patient's encounter in the ED. The BN functions only with data routinely available during the patient's encounter, which eliminates the need for additional data entry from health care providers. The management component employs the Pneumonia Severity Index risk assessment tool (10). The risk assessment tool supports physicians in the hospital admission decision. With respect to the chest x-ray interpretation the CDSS depends on input from the ED physicians. As part of the prospective evaluation, the ED physicians agreed to enter a small amount of coded data. They were only asked to enter coded data for patients suspected to have pneumonia. Because the majority of patients with a chest x-ray exam do not have pneumonia, the BN assumed in the absence of coded data that pneumonia was absent. The coded data were part of an electronic message via the radiology interface that allowed the radiologists to review the ED physicians' interpretation. ED physicians added codes for pneumonia less than 30% of the time, making ED codes an unreliable source of information for the BN. For this reason, findings from chest x-ray exams did not contribute to the BN's diagnostic evaluation in the majority of the patients. This lapse was felt to affect the BN's performance with respect to completeness of information and diagnostic accuracy.

METHODS

Setting: The ED of LDS Hospital, Salt Lake City, cares for more than 30,000 patients per year. The ED staff uses a modified version of the HELP System (7) for capturing and reviewing patient information.

Patients: All patients 18 years and older who presented to the ED during a 3-month period (January 8, 2000 – April 15, 2000) and whose chest x-ray exam was available during the patient's encounter in the ED were included. We excluded patients from the analysis who did not have a chest x-ray performed as part of their ED encounter and patients whose dictated report became available after the patient's end of the ED encounter. These patients were excluded because the NLUS would not have been able to contribute to the pneumonia diagnosis.

Study design: We analyzed data from a prospective clinical study. The NLUS determines whether the radiology report supports the presence of pneumonia on a four point ordinal scale (0 - absent; 1 - possible; 2 - probable; 3 - present). The BN was developed and trained using a dichotomous variable for the chest x-ray interpretation (0 - absent; 1 - present). If the ED physicians did not provide information about their chest x-ray interpretation, we assumed that the chest x-ray did not support pneumonia. Thus, the chest x-ray node in the BN was instantiated to 0 indicating the absence of radiologic support for pneumonia. The NLUS's four-point scale was analyzed at different cut-off values. We determined the optimal cut-off value when "pneumonia present" and "pneumonia probable" were grouped together as an indication that the chest x-ray supported the presence of pneumonia. For all study patients we replaced the BN's value for chest x-ray interpretation with the NLUS's information and recalculated the probability of pneumonia.

For the diagnosis of pneumonia we applied a previously established, clinically valid gold standard that applied a 3-step diagnostic evaluation process and involved 8 independent physicians (5 internists and 3 critical and respiratory care specialists) (11).

Outcome measures: The area under the receiver operating characteristic curve (AUC) is a measure for the overall accuracy of a diagnostic procedure (12, 13). We compared the AUC for the CDSS with and without the NLUS information (including 95% confidence intervals) and tested for statistical significance between the two ROC curves (0.05 alpha level; two-tailed) using ROCKit® (14). The probabilistic nature of the CDSS allows manipulating the threshold at which the CDSS determines the presence or absence of pneumonia. Because the CDSS acts similar to a screening test we examined the systems performance at high sensitivity levels. For this purpose we fixed the sensitivity at 90% and 95% and determined the respective specificity, the positive and negative predictive value (PV+, PV-), and the positive and negative likelihood ratios (LR+, LR-). Using the likelihood ratios we computed a standardized test effectiveness statistic δ (15):

$$\delta = (\sqrt{3} / \pi) * (\ln [\text{sensitivity} / 1\text{-specificity}] + \ln [\text{specificity} / 1\text{-sensitivity}])$$

The test effectiveness statistic sums the log of the negative and positive likelihood ratios and scales the sum with the standard deviation of the logistic normal distribution. The test effectiveness is a standardized measure of discrimination that allows comparing tests in relative and absolute terms. The statistic produces a score that indicates the number of standard deviations between positive and negative test results. Finally, we examined the number of patients with and without pneumonia whose probabilities were influenced by combining the two systems.

RESULTS

From the 1,783 patients who had a chest x-ray exam performed during the study period, the radiologist's dictated report was available during the ED encounter in 742 patients (41.6%). From the 742 patients, 45 were diagnosed with pneumonia (prevalence: 6.1%) and 697 without pneumonia according to the gold standard.

The AUC (figure) for the BN was 0.881 (95% CI: 0.822, 0.925) and for the combination of the BN with the NLUS was 0.916 (95% CI: 0.869, 0.949) (p = 0.01). The test characteristics for the BN with and without the NLUS are shown in the table with sensitivity levels fixed at approximately 90% and 95%, respectively.

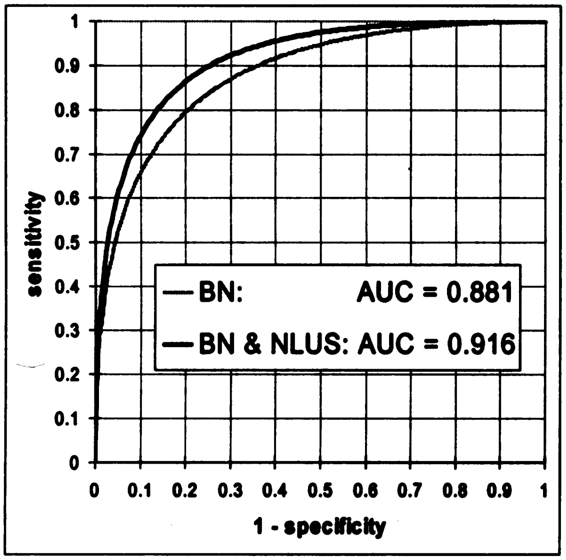

Figure: Receiver operating characteristic curve and AUC for the BN alone and the BN with the NLUS.

The test effectiveness for the BN was 1.51 (90% sensitivity) and 1.64 (95% sensitivity); the respective values for the BN with the NLUS were 1.82 and 1.98.

Among the 45 patients with pneumonia the ED physician's chest x-ray interpretation indicated the presence of pneumonia in 12 patients. In these patients the ED physicians entered the pneumonia information as coded data in the electronic message used to communicate their radiological findings to the radiologist. In 11 of these patients the NLUS concluded the presence of pneumonia from the chest x-ray reports. In these patients the probability of pneumonia was not affected because both the ED physician and the NLUS indicated that pneumonia was present. In 1 patient the NLUS determined that pneumonia was absent. This resulted in a probability decrease because the NLUS incorrectly altered the ED physician's information. In 33 patients for whom the ED physicians did not enter coded data as part of the electronic message used to communicate their radiologic interpretation to the radiologist, the NLUS concluded correctly that pneumonia was present in 29 patients. In these patients the probability increased because the NLUS provided information not provided by the ED physicians. The NLUS missed the pneumonia in the remaining 4 patients.

Among the 697 patients without pneumonia, the ED physicians incorrectly concluded the presence of pneumonia in 4 patients; in 2 of the 4 patients the NLUS correctly determined the absence of pneumonia, which resulted in a probability decrease. In the remaining 693 patients, the NLUS correctly determined that pneumonia was absent in 576 patients and incorrectly supported the presence of pneumonia in 117 patients.

DISCUSSION

This study examined whether the combination of two decision support systems that extracted and compiled information using two different methodologies increases the diagnostic accuracy for the automatic identification of patients suspected to have pneumonia. The clinical elements that were used for the diagnosis and the management of pneumonia patients were captured by the clinical information system in different data formats.

Clinicians attempt to apply the best available information for making medical decisions. Restricting the diagnostic process to data that are available in a specific data format only would limit the accuracy of decision making and influence the quality of patient care. Similarly, the information available to CDSSs should not be limited to data elements that are stored in a specific format. A potential approach to overcoming this limitation is to ask clinicians for additional and time consuming data entry and to provide information that is not accessible in the required format. However, CDSSs that extensively impact the clinicians' time are unsuitable for routine patient care. The time spent with the CDSS is time not spent with the patient.

A pneumonia diagnosis can be definitely established only if a new pneumonic infiltrate is present on the patient's chest x-ray examination. The radiologist's free text report is expected to account for all radiological data available, including previous comparison studies. However, the radiologist may be uncomfortable with this restriction to radiology exams only and often asks the physician for "clinical correlation" with the radiological findings.

Table: Test characteristics for the diagnostic system at fixed sensitivity levels of 89% and 96%.

	sensitivity	specificity	PV+	PV-	LR+	LR-
BN	0.89	0.66	0.144	0.9892	2.61	0.17
	0.96	0.47	0.105	0.9940	1.82	0.09
BN & NLP	0.89	0.77	0.202	0.9908	3.92	0.14
	0.96	0.63	0.142	0.9954	2.56	0.07

Although ED physicians may know the correct diagnosis in many pneumonia patients, their knowledge does not enter the clinical information system at a time when the information could be applied for computerized decision support. In addition, the ED physician may have access to the dictated chest x-ray report during the patient's encounter; however, the information remains unknown to the clinical information system. In such cases a NLUS can extract chest x-ray information and make it accessible to a CDSS. From this perspective, a CDSS that combines the extraction of information from clinical data and free text reports can increase the availability of computable and decidable data for computerized decision support.

Our results suggest that combining decision support methodologies can improve the performance of a diagnostic system by allowing access to more complete patient information in a computable and decidable format. The combination of the two systems has increased the accuracy in identifying patients likely to have pneumonia. Considering the low prevalence of pneumonia (6.1%) in our study population, the difference between the two AUCs (3.5%) is substantial. In 88% of pneumonia patients, the combination of the two systems resulted in a probability increase. In contrast, the combination of the two systems resulted in a probability increase for 17% of the patients without pneumonia. With the increased use of speech recognition in the radiology department, the numbers of timely available chest x-ray reports is expected to grow which could further improve the performance of the combined systems.

Our study evaluated the result of combining two decision support methodologies into a single diagnostic system. This combination of decision support methodologies could be expanded to include NLUS-based variables from other free text sources (e.g., present and past history). Such an approach could support and ease the implementation of a variety of CDSS applications, such as the computerization of clinical guidelines. These and other CDSS applications remain difficult to implement for routine patient care due to the incomplete availability of clinical data in a computable and decidable format.

In pneumonia the exchange of information between ED physicians and radiologists is frequently necessary to establish a definite diagnosis. Likewise, CDSSs need to be able to combine and correlate all patient information available in the computerized patient record independent of the format used to store this information.

References

1. Tversky A, Kahneman D. The framing of decisions and the psychology of choice. Science 1981211:453-8.
2. Hunt DL, Haynes RB, Hanna SE, Smith K. Effects of computer-based clinical decision support systems on physician performance and patient outcomes: a systematic review. JAMA 1998;280:1339-46.
3. Balas EA, Austin SM, Mitchell JA, Ewigman BG, Bopp KD, Brown GD. The clinical value of computerized information services. A review of 98 randomized clinical trials. Arch Fam Med. 1996;5:271-8.
4. Barnett GO, Winickoff RN. Quality assurance and computer-based patient records. Am J Public Health 1990;80:527-8.
5. Aronsky D, Haug PJ. Automatic identification of patients eligible for a pneumonia guideline. Proc AMIA Symp. 2000;:12-6.
6. Fiszman M, Haug PJ. Using medical language processing to support real-time evaluation of pneumonia guidelines. Proc AMIA Symp. 2000;:235-9.
7. Gardner RM, Pryor TA, Warner HR.The HELP hospital information system: update 1998. Int J Med Inf. 1999;54:169-82.
8. Haug PJ, Koehler S, Lau LM, Wang P, Rocha R, Huff SM. Experience with a mixed semantic/syntactic parser. Proc Annu Symp Comput Appl Med Care. 1995;:284-8.
9. Chapman WW, Aronsky D, Fiszman M, Haug PJ. Contribution of a speech recognition system to a computerized pneumonia guideline in the emergency department. Proc AMIA Symp. 2000;:131-5.
10. Fine MJ, Auble TE, Yealy DM, Hanusa BH, Weissfeld LA, Singer DE, et al. A prediction rule to identify low-risk patients with community-acquired pneumonia. NEJM. 1997;336:243-50.
11. Aronsky D, Chan KJ, Haug PJ.Evaluation of a Computerized Diagnostic Decision Support System for Patients with Pneumonia: Study Design Considerations. J Am Med Inform Assoc. 2001 (in press).
12. Metz CE. Basic principles of ROC analysis. Seminars in Nuclear Medicine. 1978;8:283-98.
13. Hanley JA, McNeil BJ. The meaning and use of the area under a receiver operating characteristic (ROC) curve. Radiology. 1982;;143:29-36.
14. ROCKIT (0.9B Beta Version). Charles E. Metz. Dept. of Radiology, Univ. of Chicago.
15. Blakeley DD, Oddone EZ, Hasselblad V, et al. Noninvasive carotid artery testing. A meta-analytic review. Ann Intern Med.1995;122:360.